The International Journal of Business Management and Technology, Volume 10 Issue 07 July 2026
ISSN: 2581-3889

Research Article Open Access

Global Drivers of Food Prices: The Roles of Energy Prices, the U.S. Dollar, and Supply Chain Pressures

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Abstract: Global food prices have become increasingly exposed to macroeconomic and geopolitical disturbances, yet limited empirical evidence explains how energy markets, exchange rate movements, and supply chain disruptions jointly influence food price dynamics. This study examines the combined effects of global energy prices, the Broad U.S. Dollar Index, and the Global Supply Chain Pressure Index (GSCPI) on the FAO Food Price Index using monthly observations covering January 2006 to May 2026. An Autoregressive Distributed Lag (ARDL) framework is employed to distinguish between long-run equilibrium relationships and short-run adjustments among the variables.

The empirical findings indicate that energy prices constitute the dominant long-run determinant of global food prices, with sustained increases in energy costs translating into persistently higher food prices over time. By contrast, appreciation of the U.S. dollar exerts a significant negative influence only in the short run, while the aggregate impact of global supply chain pressures remains statistically limited. Additional robustness analyses—including alternative energy measures, crisis-period controls, and disaggregated FAO commodity indices—confirm the stability of the baseline results and reveal substantial differences across commodity groups, particularly for vegetable oils, sugar, and cereals.

By integrating energy markets, international monetary conditions, and global supply chain pressures into a unified empirical framework, this study provides a more comprehensive perspective on the mechanisms driving global food prices. The findings contribute to the literature on food price formation and offer policy implications for improving food market resilience under conditions of heightened global uncertainty.

Keywords: Food price dynamics; Global food prices; Energy prices; U.S. Dollar Index; Global Supply Chain Pressure Index (GSCPI); ARDL

I. Introduction

Increasing importance has been attached to international food prices in recent years because of the food security and inflation issues. Three large price increases took place in the international food market in the last two decades: the food crisis in 2007-2008, the food price spike in 2010-2011, and the most recent price increase after the COVID-19 pandemic and the war between Russia and Ukraine in 2021-2022. In the latter case, prices in developing countries increased significantly faster than consumer prices, raising the concerns about food affordability (Headey & Hirvonen, 2023).

In spite of the general improvement in international agricultural production in 2025, food markets in the world remain uncertain. According to the report by FAO (2025), positive prospects are available for several important crops such as wheat, coarse grains, rice, and oil seeds. However, uncertainty still surrounds the food market because of the changes in the trade environment, policy uncertainty, and cost pressures. Furthermore, it is stated that higher energy prices still affect the market for fertilizers, in spite of the recovery in the production of fertilizers and stabilization of global trade.

Similarly, the report by the World Bank (2025) mentions geopolitical tensions, trade uncertainty, energy market, and weather risks among the most important factors influencing commodity market conditions. Thus, all the above-mentioned trends demonstrate the fact that changes in international food prices are affected by economic and geopolitical factors along with agricultural factors.

Thus, increasing complexity of the international food markets makes the analysis of international food price changes more difficult than several decades ago. According to the OECD–FAO Agricultural Outlook (2025-2034), interactions between production, consumption, trade, macroeconomic and policy environment play more important role in development of agricultural markets than agriculture itself. Moreover, the report states that future market conditions will depend on both fundamentals of supply and demand and wider economic environment with uncertainties associated with international trade and policies.

Empirical studies recently conducted have enlarged the list of factors used for food price analysis. Zmami and Ben-Salha (2023) state that oil prices, fertilizer prices, global economic activity, and geopolitical risk are important factors explaining the international food price volatility; however, these factors have different impact on different food commodity groups under different market conditions. Also, it is noted that these factors were mostly analyzed separately or for certain commodities, in spite of the increasing significance of multiple shocks appearing in the global economy simultaneously.

In line with this view, the World Bank (2025) notes that markets for agricultural commodities are always exposed to geopolitical risks, trade policies, developments in the energy market, and weather risks. This means that an investigation into the dynamics of global food prices requires an understanding of various transmission mechanisms working simultaneously in international commodity markets.

Building on the discussion above, this study investigates the key drivers of global food prices by jointly examining global energy prices, the Broad U.S. Dollar Index, and the Global Supply Chain Pressure Index (GSCPI) in relation to the FAO Food Price Index. Monthly observations covering the period from January 2006 to May 2026 are analysed using the Autoregressive Distributed Lag (ARDL) methodology. This approach is well suited for evaluating both the long-run equilibrium relationships and the short-run dynamics among the selected variables. By integrating three major global transmission channels—energy markets, international monetary conditions, and supply chain disruptions—the analysis provides a broader explanation of the forces shaping global food price movements than studies focusing on a single transmission mechanism.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and establishes the theoretical foundation of the study. Section 3 describes the dataset and research methodology. Section 4 presents the empirical estimation strategy and reports the main findings, while Section 5 provides a series of robustness analyses. Section 6 discusses the results in relation to previous research and highlights their policy implications. The final section concludes the paper and outlines potential directions for future research.

II. Literature Review

2.1. Theoretical Background on Global Food Price Formation

The global food price formation has received considerable attention in agricultural economics due to its influence on food security, inflation, international trade, and macroeconomic stability. Food price shocks negatively affect consumers' purchasing power, and this effect is especially strong in developing countries where food is a major expense category. Some notable instances include the global food crisis in 2007–2008 and more recent instances related to the COVID-19 outbreak and the war between Russia and Ukraine. In both cases, the shocks in food prices quickly spread across national borders and caused serious effects (Headey & Fan, 2008; Headey & Hirvonen, 2023).

Initially, food prices were attributed to market supply and demand factors. However, with the increasing integration of agricultural markets, food price formation has become more complicated. According to Rezitis and Sassi (2013), there are many different interrelated determinants of the prices of internationally traded food, including food production, food stock, international trade, exchange rates, energy markets, government policies, and expectations of the market participants. The fact that agricultural goods are sold in globally integrated markets means that food price shocks may spread through trade and financial linkages and influence international prices.

A more comprehensive analysis is provided by Tadesse et al. (2014). In particular, the researchers argue that it is impossible to attribute food price movements to one specific factor. They divide the price drivers into three categories – root drivers related to long-term supply-demand fundamentals, conditional drivers comprising energy prices, exchange rates, trade policies, and macroeconomic conditions, and internal market drivers associated with inventory changes, speculation, and financial markets changes. Similarly, von Braun and Tadesse (2012) note that price spikes emerge in the situations when several shocks happen simultaneously and not individually.

Recent research also highlights the role of multiple global factors in food prices formation. For instance, in their study of international food price volatility, Zmami and Ben-Salha (2023) identify oil prices, fertilizer prices, global economic activity, and geopolitical risks as some important determinants of the food price movement; however, their impact differs among different groups of food commodities. It means that food price dynamics is affected not only by agricultural market fundamentals but also by global economic and geopolitical developments.

In summary, the existing literature suggests that the global food prices are formed under the influence of interaction of the structural market fundamentals and global shocks happening simultaneously in the international markets. Among the factors mentioned above, energy prices, exchange rate changes, and global supply chain conditions attract the increasing attention as the main channels through which global shocks affect food prices. More information on these factors will be presented in the following sections.

2.2. Energy Prices and Food Prices

The prices of energy are well-known drivers of global food prices, as energy is one of the main inputs in agriculture. Crude oil and oil-based products are commonly used for the operation of agricultural equipment, irrigation, production of fertilizers, food processing, storage, and transportation. As a result, the rising prices of energy increase the cost of production and distribution of goods that are transferred to the agricultural commodity prices and, consequently, to food prices (Shokoohi & Saghaian, 2022; Khan et al., 2022).

Earlier studies illustrate this relationship with the help of several transmission mechanisms. Shokoohi and Saghaian (2022) state that the increased cost of crude oil directly influences the cost of agricultural production due to the use of energy-intensive inputs such as fuel, fertilizers, and transportation. Moreover, the scholars argue that the variations in the cost of oil influence the inflation rates, economic growth rates, and exchange rates that, in turn, can influence food prices. Similarly, Khan et al. (2022) point out that oil is one of the key inputs in the production of agricultural products. In addition, the scholars note the biofuels production as another way of energy-food transmission. According to the authors, the higher cost of oil raises the demand for biofuels' raw materials such as maize and sugar crops that decreases the supply of those goods for food purposes and affects their prices positively.

However, recent research reveals that the connection between the cost of energy and food prices goes beyond a mere cost-push mechanism. By using global food price indices and indices of specific commodities, Sun et al. (2023) show that oil price shock, oil supply shock, and oil demand shock are among the sources of changes in food prices but they have different impact on different kinds of commodities. For instance, their research demonstrates that dairy, meat, cereals, soybeans, and other agricultural commodities are sensitive to oil market shocks to various extents. Thus, the scholars identify exchange rate movements and financialization of commodity markets as additional links between oil and food markets.

Finally, the latest studies continue the same line of thought by arguing that the prices of energy should be analyzed in combination with other factors. For example, Zmami and Ben-Salha (2023) investigate the joint effect of oil prices, fertilizer prices, global economic activity, and geopolitical risk on international food price volatility and find that oil prices are still a significant factor that influences food prices despite the heterogeneity across different kinds of food commodities and market conditions. Similar findings were reported by Hamouda (2024). Namely, the author found the asymmetry in the long-run relationship between the price of oil and food prices meaning that food prices react differently to the increasing and decreasing oil prices.

To sum up, the current literature identifies the prices of energy as one of the main determinants of global food prices through their impact on agricultural costs, biofuels demand, and macroeconomic conditions. However, the literature suggests that the impact of energy prices on the food prices differs across different kinds of food products and market conditions.

2.3. Exchange Rate Effects on Food Prices

Exchange rate has become a growing determinant of global food prices since agricultural products are mostly priced in U.S. dollars. A considerable share of international trade is settled using dollars rather than currencies of export countries. Therefore, U.S. dollar has gained a leading place in commodity markets around the world. As a result, the dynamics of U.S. dollar value influences international commodity prices, costs of imports and exports, and trade volumes beyond just bilateral exchange rates (Boz et al., 2017). Along with the role of an invoicing currency, the U.S. dollar plays a critical part in trade financing. According to Bruno and Shin (2019), the appreciation of U.S. dollar leads to increasing cost of financing since credit conditions in terms of U.S. dollar tighten, influencing international trade and value chains. Thus, all these processes mean that exchange rate dynamics may have an impact on international food prices through two channels – pricing and financing.

However, the transmission of global food prices to domestic markets is neither complete nor automatic. Analysis conducted by Kohlscheen (2022) based on data from 35 countries shows that after excluding exchange rate changes pass-through from international to domestic food prices is relatively low during one-year period. In addition, the author finds out that domestic food price inflation is driven not only by exchange rates but also by other macroeconomic variables such as inflation expectations and domestic economic activity. Thus, exchange rates play a role of an important mechanism of transmission while not being the only determinant of domestic food prices.

There are some other empirical studies dealing with the role of exchange rates in food price dynamics. Kartal and Depren (2023) find that domestic food prices are affected by both international and national shocks with the importance of one of them varying through time depending on market situation. In particular, their findings reveal that movements in exchange rates operate as a mechanism of transmission of international shocks to domestic food markets. Similarly, Ertuğrul and Seven (2023) examine the impact of international prices on Turkish food prices and prove that exchange rate dynamics account for an increase in difference between international and domestic food prices, whereas oil prices narrow the gap between them.

Importance of exchange rate dynamics is confirmed by Chadwick (2023) who examines the main determinants of food price increases following global food crises and finds that exchange rate movements are among the major factors along with increases in oil prices, trade policies, financial speculation, biofuel demand, and stocks. Besides, the author proves that international trade shocks have important consequences for retail food prices demonstrating a high degree of connection between international and domestic markets.

Thus, recent academic literature shows that exchange rate movements – in particular movements of the U.S. dollar – are crucial for formation of international food prices influencing commodity pricing, international trade, and transmission of shocks. These findings give strong theoretical rationale to include Broad U.S. Dollar Index into the regression model in the present study.

2.4. Global Supply Chain Disruptions and Food Prices

Food supply systems operate using complex chains of agricultural production, processing, storage, transportation, trade, consumption, and disposal activities. Due to the inherent connection between these processes, any disruption in the supply chain will affect the availability, quality, distribution, and price of food products. According to Rojas-Reyes et al. (2024), who reviewed 74 related studies, the disruptions in food supply chains are characterized as disturbances in the normal movement of food products and include such sources of disruption as climate-related events, natural disasters, pandemics, conflicts, and political instabilities. Moreover, the study shows that logistics and infrastructure disruptions are considered one of the most often researched aspects because of its direct impact on food availability, performance of operations, and price.

In order to estimate the impact of supply chain pressures, Benigno et al. (2022) have developed the Global Supply Chain Pressure Index (GSCPI). It is a composite index, which combines international shipping costs and Purchasing Managers' Index (PMI) data on supplier delivery times, backlogs, and inventories in the major trading economies. This index estimates all the dimensions of global supply chains in contrast to any other indicator which covers only one aspect of supply chains. The use of this index has allowed the authors to demonstrate that an increase in supply chain pressures leads to an essential contribution to producer price inflation as the effect of transmission of supply shocks through the production networks is gradual.

Further, Andriantomanga et al. (2023) argue that an increase in international transportation costs, supplier delivery times, and lack of intermediate inputs increase production costs and thus inflation. In addition, supply shocks are especially dangerous for economies, which are importers of goods and intermediate inputs.

The existing research also shows that disruptions in supply chains usually happen together with other geopolitical or economic shocks. Asadollah and Farzanegan (2024) state that geopolitical risk influences inflation due to disruptions in global production and logistics networks. Using GSCPI as the indicator of supply-side constraints, the authors prove that geopolitical risks lead to an increase in supply chain pressures which, in their turn, lead to the increase in inflation. Hence, the consequences of geopolitical events not only affect the energy market but also disrupt international production and logistics networks.

The increasing role of supply chains is also supported by recent empirical evidence. In their study, Toledo and Duncan (2024) show that indicators of international supply chains considerably enhance the performance of domestic food price inflation forecasts in case of global crises, namely during the COVID-19 pandemic. Similarly, Wang (2024) demonstrates that supply chain shocks cause sustained increase in consumer and producer prices as well as reduction in industrial production. Besides, supply chain shocks along with energy and food price shocks are the key factors which led to recent inflation period following the COVID-19 pandemic and Russia–Ukraine conflict.

2.5. Research Gap and Contribution

It should be noted that the available literature has made an essential contribution to the knowledge about the determinants of global food price dynamics by exploring such factors as the impact of energy prices, exchange rates, geopolitical risks, and supply chain disruptions on the dynamics of global food prices. However, these factors have mostly been investigated separately or independently in different empirical frameworks. For example, when investigating the influence of oil prices, researchers tend to consider the impact of fluctuations in the energy market on the dynamics of agricultural commodities' prices. Studies of exchange rates tend to focus on exchange rate pass-through or on the influence of the US dollar on international trade and food prices in the respective countries. Recently, GSCPI (Global Supply Chain Pressure Index) has started to be used as a measure that accounts for the effect of supply chain disruptions on inflation. Nevertheless, this new strand of literature is predominantly focused on overall inflation rather than on global food prices.

Another drawback of the previous research on global food prices is that it mostly focuses on analyzing individual agricultural commodities or country-specific food price indices. Although such studies may offer useful information, they can be ineffective in terms of capturing the common global factors that affect international food prices. Therefore, relatively little attention has been paid to the investigation of the interaction of energy market conditions, international monetary conditions, and global supply chain pressures on the dynamics of the FAO Food Price Index that provides one of the most comprehensive measures of changes in global food prices.

To fill this gap in the literature, this paper considers the interaction of three major transmission channels suggested by the existing research in one unified empirical framework. It includes the analysis of the impact of Brent crude oil prices (energy market channel), the Broad U.S. Dollar Index (international monetary conditions and commodity pricing), and GSCPI (global supply chain pressures) on the dynamics of the FAO Food Price Index using the ARDL approach to distinguish the effects in the short and long run.

The consideration of all three transmission channels in one empirical framework fills the gap in the literature since these factors have been mostly investigated independently or in different empirical frameworks.

III. Data

The empirical exercise uses monthly data ranging from January 2006 to May 2026, which consists of 245 monthly observations in total. The starting point is selected based on the earliest monthly data observation of the broad U.S. dollar index; however, the window includes the events responsible for the bulk of the variability utilized in the analysis, which include the global financial crisis of 2008, commodity price spikes of 2010–2011, COVID-19-induced disruption of the supply chain in 2020–2021, and Russia-Ukraine military conflict in 2022. The dependent variable used is the FAO Food Price Index, and the independent variables capture the three main drivers affecting movements in global food prices: energy prices, the external value of the dollar in which food commodities are denominated, and the strain on the supply chain globally. The peak of the food index occurs in March 2022 with the onset of the Russian invasion of Ukraine, while the supply chain pressure index peaks in December 2021.

3.1. Variable Definitions and Descriptive Statistics

Table 1 summarises the variables employed in the empirical analysis together with their definitions and data sources.

Table 1. Variable definitions and sources

Variable	Definition	Unit	Source
Food price index	FAO nominal Food Price Index	index, 2014–16 = 100	FAO
Energy price index	Global energy price index (oil, gas, coal)	index, 2016 = 100	IMF (via FRED)

Brent	Global price of Brent crude oil	USD per barrel	IMF (via FRED)
Dollar index	Nominal Broad U.S. Dollar Index	index, Jan 2006 = 100	Federal Reserve (via FRED)
GSCPI	Global Supply Chain Pressure Index	std. dev. from mean	FRB New York

Notes: The energy price index and Brent enter as alternative energy proxies; the broad energy index is used in the baseline and Brent in robustness. In estimation the food, energy, Brent and dollar series are log-transformed; GSCPI, which admits negative values, enters in levels.

Table 2. Descriptive statistics (N = 245; monthly, 2006:01–2026:05)

Variable	Mean	SD	Min	Median	Max
Food price index	109.83	18.88	69.78	112.79	160.22
Energy price index	175.95	55.45	55.89	169.23	376.41
Brent (USD/barrel)	77.30	23.22	26.85	74.04	133.59
Dollar index	106.32	12.32	86.32	109.98	128.84
GSCPI	0.20	1.10	−1.58	−0.07	4.44

Table 3. Correlation matrix

	ln Food	ln Energy	ln Brent	ln Dollar	GSCPI
ln Food	1.000	0.705	0.668	0.054	0.325
ln Energy	0.705	1.000	0.947	−0.354	0.095
ln Brent	0.668	0.947	1.000	−0.465	−0.030
ln Dollar	0.054	−0.354	−0.465	1.000	0.305
GSCPI	0.325	0.095	−0.030	0.305	1.000

Collectively, the descriptive statistics reveal three aspects of the dataset that will play a role in the econometric specification to be elaborated in the next section. First, both prices and indices are persistent processes, where first-order autocorrelation coefficients of the food, energy, and dollar indices range between 0.97 and 0.99, meaning that they follow trends rather than fluctuate around the mean value. It is the first aspect that must be taken into account when conducting estimation, because regressing on persistent variables using levels might lead to spurious inference; thus, the approach involves unit root testing and bounds testing for cointegration. The index of supply chain pressure is an exception, as it is less persistent (0.93) and has an average value of about zero.

Second, the two energy measures are near-collinear (Table 3): the log energy price index and log Brent correlate at 0.95, so they act as substitutes rather than distinct regressors. To avoid redundancy the broad energy price index is retained as the baseline—it embeds natural gas and coal alongside crude oil and so captures more fully the fertiliser and transport-cost channels through which energy reaches food—while Brent is reserved for robustness. Third, the dollar's unconditional correlation with food prices is essentially nil (0.05), even though food co-moves strongly with energy (0.71). The near-zero level raw correlation, however, is meaningful: since agricultural products are priced in US dollars, the impact of the exchange rate gets muddied in level variables due to the common trend component in both the dollar and the other explanatory variables, which have correlations to the dollar between −0.35 and −0.47. In order to understand its effect, a multivariate model conditioning on the energy and on the dynamics of the level variable is needed, and thus the rationale behind the following error correction approach is provided. The supply chain pressure has a small but positive correlation with the food price (0.33), in line with the expected sign in the case of a cost-push factor. These are only unconditional correlations that confuse the trend, energy, and dollar components, but still foreshadow the estimation task ahead: separating the long-term food-energy correlation from the short-term dollar and supply chain effects.

IV. Methodology

Selecting an appropriate econometric framework is particularly important when analysing global food prices because the explanatory variables capture different dimensions of the global economy and exhibit different stochastic properties. Energy prices, exchange rates, and supply chain indicators may not share the same order of integration or adjustment speed. Consequently, the empirical strategy should be capable of modelling both long-run equilibrium relationships and short-run dynamics without imposing unnecessarily restrictive assumptions on the data-generating process.

The ARDL methodology is selected because it is well aligned with both the characteristics of the data and the objectives of the analysis. Unlike many conventional cointegration methods, it can accommodate variables with mixed orders of integration, provided that none is integrated beyond I(1). This flexibility makes the approach particularly appropriate for the present dataset. A further advantage of the ARDL model is that it estimates long-run equilibrium relationships and short-run adjustment dynamics within a unified framework. As a result, it enables the distinction between persistent and transitory effects of the explanatory variables on global food prices. Moreover, the ARDL approach has been widely employed in empirical research involving relatively small and medium-sized samples. Its proven performance in studies of energy and commodity price relationships provides additional justification for its use in the present analysis.

4.1. Empirical framework

The empirical analysis employs the Autoregressive Distributed Lag (ARDL) bounds-testing methodology to investigate the transmission of energy price movements to global food prices (Ibrahim, 2015; Zmami & Ben-Salha, 2019). This approach is particularly appropriate for the present study because it accommodates variables with different integration properties without requiring a common order of integration. Specifically, the ARDL framework can be applied when the regressors are integrated of order zero, order one, or cointegrated, provided that none exhibits integration beyond I(1). This flexibility makes it possible to estimate the effects of the stationary, mean-reverting supply chain pressure index together with trending price variables within a unified empirical framework. Second, it recovers the long-run equilibrium relationship and the short-run error-correction dynamics from a single conditional equation, which is precisely the decomposition of interest here. The baseline two-variable food–energy specification is extended in two directions suggested by the literature: the external value of the U.S. dollar, which Nazlioglu and Soytas (2012) identify as a first-order determinant of dollar-denominated agricultural prices, is included as a second driver, and global supply-chain pressure is captured by the index proposed by Benigno et al. (2022). Because the estimation window encompasses the COVID-19 disruption and the 2022 Russia–Ukraine war, and because the food–energy relationship is known to be susceptible to parameter shifts around such episodes (Al-Maadid et al., 2017), the specification is subjected to explicit parameter-stability testing and to crisis dummies.

4.2. Model specification

Let *FPI*, *EN* and *USD* denote the food price index, the energy price index and the broad U.S. dollar index, each expressed in natural logarithms, and let *GSCPI* denote the supply-chain pressure index, which is entered in levels because it takes negative values. The conditional (unrestricted) error-correction representation of the ARDL(p, q_1, q_2, q_3) model is written as

$$\Delta \ln FPI_t = \alpha + \Sigma_i \varphi_i \Delta \ln FPI_{t-i} + \Sigma_j \beta_j \Delta \ln EN_{t-j} + \Sigma_k \gamma_k \Delta \ln USD_{t-k} + \Sigma_l \lambda_l \Delta GSCPI_{t-l} + \rho_0 \ln FPI_{t-1} + \rho_1 \ln EN_{t-1} + \rho_2 \ln USD_{t-1} + \rho_3 GSCPI_{t-1} + \varepsilon_t \quad (1)$$

where Δ is the first-difference operator, α is a constant, the summations with coefficients φ, β, γ and λ capture the short-run dynamics over p and q_m lags selected empirically, and the lagged level terms ρ_0–ρ_3 carry the long-run information. The existence of a long-run (cointegrating) relationship is examined through the bounds F-test of the joint null

$$H_0: \ \rho_0 = \rho_1 = \rho_2 = \rho_3 = 0 \quad (2)$$

against the alternative that at least one coefficient is non-zero. The computed statistic is compared with the lower- and upper-bound critical values tabulated for the case of an unrestricted intercept and no trend: a statistic above the upper [I(1)] bound indicates cointegration, one below the lower [I(0)] bound indicates its absence, and an intermediate value is inconclusive (Ibrahim, 2015; Zmami & Ben-Salha, 2019). When a levels relationship is supported, the long-run elasticities are obtained from the lagged-level coefficients as

$$\theta_m = -\rho_m / \rho_0 , \quad m = 1, 2, 3 \quad (3)$$

and the model is re-expressed in error-correction form as

$$\Delta \ln FPI_t = \alpha + \Sigma_i \varphi_i \Delta \ln FPI_{t-i} + \Sigma_j \beta_j \Delta \ln EN_{t-j} + \Sigma_k \gamma_k \Delta \ln USD_{t-k} + \Sigma_l \lambda_l \Delta GSCPI_{t-l} + \psi\, ECT_{t-1} + \varepsilon_t \quad (4)$$

where $ECT_{t-1} = \ln FPI_{t-1} - (\theta_1 \ln EN_{t-1} + \theta_2 \ln USD_{t-1} + \theta_3 GSCPI_{t-1})$ is the one-period-lagged residual from the estimated long-run relationship and ψ is the speed-of-adjustment coefficient. A negative and statistically significant ψ confirms that departures from long-run equilibrium are corrected over subsequent periods, with its absolute magnitude measuring the monthly rate of adjustment.

Where the bounds test does not support a joint levels relationship among all series, the short-run drivers are estimated directly from the stationary first-difference model

$$\Delta \ln FPI_t = c + \beta_0 \Delta \ln EN_t + \gamma_0 \Delta \ln USD_t + \lambda_0 \Delta GSCPI_t + \varphi_1 \Delta \ln FPI_{t-1} + \varepsilon_t \quad (5)$$

in which every term is stationary and the spurious-regression problem is therefore avoided. This specification is complemented by an Engle–Granger error-correction model that augments equation (5) with the lagged residual from the food–energy long-run regression, so that the long-run energy anchor and the short-run influence of the dollar and of supply-chain pressure are estimated within a single equation.

4.3. Estimation and diagnostic testing

The estimation strategy begins by identifying the stochastic properties of the variables. Although the ARDL bounds-testing approach can accommodate regressors integrated of different orders, it is not applicable when any variable is integrated beyond I(1). Therefore, the order of integration is verified using the Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and KPSS unit root tests applied to both level and first-difference series (Ibrahim, 2015). Following the stationarity assessment, the optimal lag structure is determined according to the Akaike Information Criterion (AIC), allowing a maximum of twelve monthly lags. Short-run coefficients are estimated using heteroskedasticity- and autocorrelation-consistent (HAC) standard errors following the Newey–West correction to account for the characteristics of monthly macroeconomic time-series data. Model adequacy is evaluated through a comprehensive set of post-estimation diagnostic tests. Residual serial correlation is examined using the Breusch–Godfrey LM test, conditional heteroskedasticity is assessed by the ARCH LM test, residual normality is verified with the Jarque–Bera statistic, and functional specification is checked using the Ramsey RESET test. In addition, parameter stability is investigated by means of the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests to ensure that the estimated coefficients remain stable throughout the sample period.

The robustness of the findings is examined along four dimensions. First, the Brent crude oil price is substituted for the broad energy index to verify that the results do not hinge on the choice of energy proxy. Second, the real (deflated) food price index replaces the nominal index as the dependent variable, isolating the relationship from common inflation trends. Third, step dummies for the COVID-19 disruption and the 2022 war are added to confirm that the estimates are not driven by these outlier episodes, a concern motivated directly by the structural-break evidence of Al-Maadid et al. (2017). Finally, the model is re-estimated for the five FAO sub-indices — cereals, vegetable oils, meat, dairy and sugar — to trace the heterogeneous transmission of energy and supply-chain shocks across the components of the aggregate index, in the spirit of the disaggregated analysis of Zmami and Ben-Salha (2019).

A clarification on the two energy measures is in order, since they are deliberately never used together. The broad energy price index and the Brent crude price are alternative proxies for the same underlying construct and are near-collinear over the sample, so entering both in one equation would be uninformative. The broad index therefore serves as the baseline regressor throughout, because it embeds natural gas and coal alongside crude oil and so captures the fertiliser and transport-cost channels more completely, while Brent appears only as an alternative specification in the robustness analysis. Brent is nonetheless subjected to the same unit-root testing as the baseline series, since its integration order must be established before it can be used in any estimation.

V. Results

5.1. Integration order

The unit-root tests confirm the mixed integration structure anticipated in the descriptive analysis. The augmented Dickey–Fuller test does not reject a unit root in the levels of the food, energy and dollar series, and the KPSS test rejects stationarity for the food and dollar indices; together these place the (log) food, energy and dollar series in the I(1) class, with log Brent borderline. The supply-chain index is stationary in levels, I(0), in keeping with its construction as a mean-reverting deviation gauge. First-differencing removes the unit root in every case and no series is integrated of order two, so the bounds-testing procedure is applicable.

Table 4. Unit-root tests (p-values)

Variable	ADF (c)	ADF (c,t)	KPSS	Δ ADF (c)	Order
ln Food	0.058	0.173	0.029	0.000	I(1)
ln Energy	0.055	0.194	0.100	0.000	I(1)

ln Brent	0.012	0.053	0.100	0.000	I(0)
ln Dollar	0.744	0.080	0.010	0.000	I(1)
GSCPI	0.020	0.040	0.024	0.000	I(0)

Notes: entries are p-values. ADF = augmented Dickey–Fuller (c: intercept; c,t: intercept and trend); KPSS null is stationarity. Δ ADF (c) is the ADF test on first differences. Brent is reported because it is used as an alternative energy proxy in the robustness analysis (Table 10); it never enters the same equation as the broad energy index. No series is I(2), validating the ARDL bounds approach.

5.2. Cointegration

The bounds F-tests deliver a clear and instructive pattern. The food and energy indices share a long-run relationship: the statistic of 5.32 exceeds the upper I(1) critical bound at the 5% level. When the dollar or the supply chain index is added to the specification, the test statistic loses power; it drops to 2.50 when the dollar is included and 2.15 in the complete specification, dropping below the lower bound and suggesting that there is no evidence of cointegration in the extended specification. This does not mean that these two variables do not have any importance; adding a non-cointegrating I(1) variable to the equation automatically lowers the joint test statistic. This suggests that the long-run relationship is the one between food and energy, whereas the other two function in the short run.

Table 5. ARDL bounds tests (case III; 5% critical values)

Specification	F	I(0)	I(1)	Verdict
Food ~ Energy	5.32	3.80	4.81	Cointegrated
Food ~ Energy + Dollar	2.50	3.23	4.32	No cointegration
Food ~ Energy + GSCPI	3.64	3.23	4.32	Inconclusive
Food ~ Energy + Dollar + GSCPI	2.15	2.88	4.01	No cointegration

Notes: bounds F-test of Pesaran-Shin-Smith. I(0) and I(1) are the 5% lower and upper critical bounds.

5.3. Long-run and error-correction estimates

The long-run and short-run estimates are reported separately in Tables 6 and 7. The long-run elasticity of energy is 0.385 (t = 8.86): a 10% permanent rise in the energy index is associated with a 3.9% rise in the food index over the long run. This incomplete pass-through echoes the evidence of Ibrahim (2015), who likewise finds food prices respond to energy by well under unity, and is consistent with energy being one input cost among several along the food supply chain.

Turning to the short-run dynamics in Table 7, the error-correction term is correctly signed and significant ($\psi = -0.022$, t = −2.29), confirming reversion toward the food–energy path, though the pace is slow: about 2% of any disequilibrium is corrected per month. The short run is dominated by the dollar, with a 1% appreciation of the broad dollar coinciding with a 0.68% fall in the food index within the month (t = −6.10), the largest and most precisely estimated effect in the model. This negative sign is exactly that predicted for a dollar-denominated commodity and matches the first-order role of the dollar documented by Nazlioglu and Soytas (2012). Contemporaneous energy changes enter positively (0.089), supply-chain pressure only marginally (0.005), and food prices display strong own-momentum (0.369). The weak aggregate supply-chain effect is itself consistent with Benigno et al. (2022), whose index transmits more strongly to upstream producer prices than to a downstream consumer food basket.

Table 6. Long-run (cointegrating) relationship between food and energy prices

Variable	Coefficient	HAC t
ln Energy	0.385***	8.86
Constant	2.710***	11.76

*Notes: dependent variable is ln Food. Estimated over the cointegrating food–energy pair identified in Table 5 (bounds F = 5.32, above the 5% upper bound of 4.81); ARDL(2,1) selected by AIC. N = 245. HAC (Newey–West) t-statistics. *** p<0.01.*

Table 7. Short-run dynamics and error correction (dependent variable: Δ ln Food)

Regressor	Coefficient	HAC t
ECT (−1)	−0.022**	−2.29
Δ ln Energy	0.089***	3.74
Δ ln Dollar	−0.681***	−6.10
Δ GSCPI	0.005	1.63
Δ ln Food (−1)	0.369***	6.83

*Notes: ECT (−1) is the lagged residual from the long-run relationship in Table 6. N = 243; R^2 = 0.53. HAC (Newey–West) t-statistics. *** p<0.01, ** p<0.05, * p<0.10.*

5.4. Diagnostics and stability

The specification is sound on the dimensions that matter for inference. The Breusch–Godfrey test finds no residual autocorrelation (p = 0.99) and the Ramsey RESET no functional-form misspecification (p = 0.14). The ARCH and Jarque–Bera tests do flag conditional heteroskedasticity and fat-tailed, non-normal residuals — an unavoidable feature of monthly commodity data spanning the 2008, 2020 and 2022 shocks — but both are accommodated by the Newey–West standard errors used throughout and neither biases the coefficient estimates. Parameter stability is assessed graphically in Figure 1: both the CUSUM and the CUSUM-of-squares statistics remain inside their 5% confidence bands over the whole sample, indicating that the estimated relationships did not shift despite the turbulence of the estimation window.

Table 8. Diagnostic tests

Test	Statistic	p-value
Breusch–Godfrey LM (12 lags)	3.75	0.988
ARCH LM (12 lags)	33.53	0.001
Jarque–Bera (normality)	73.30	0.000
Ramsey RESET (power 2)	2.15	0.144

Notes: p-values reported. Tests are applied to the residuals of the error-correction model in Table 7. Parameter stability is reported separately in Figure 1.

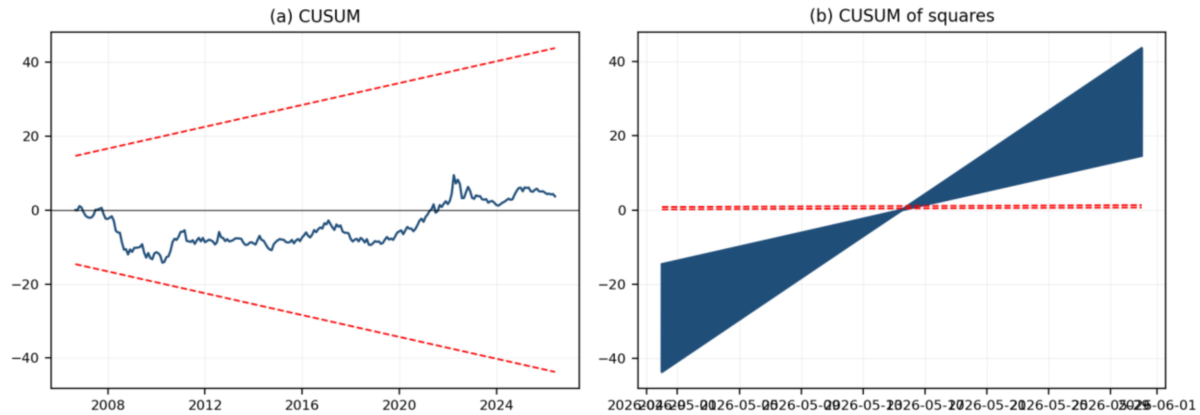

Figure 1. CUSUM and CUSUM-of-squares stability tests

Notes: recursive residual statistics from the error-correction model in Table 7; dashed lines are the 5% critical bands. Both statistics remain within the bands over the full sample.

5.5. Robustness

Robustness is assessed in two stages, addressing the long-run and the short-run components of the model separately. Because the long-run relationship rests on a single cointegrating equation estimated by least squares, it is re-estimated with two semiparametric cointegrating estimators that correct for endogeneity and residual serial correlation: fully modified OLS (FMOLS) and dynamic OLS (DOLS). Table 9 shows the three estimates of the long-run energy elasticity to be closely aligned, ranging only from 0.363 to 0.407 and in every case significant at the 1% level, so the baseline figure of 0.385 is not an artefact of the estimator.

Table 9. Long-run robustness: alternative cointegrating estimators (dependent variable: ln Food)

Estimator	ln Energy	t-statistic	N
ARDL / OLS (baseline)	0.385***	8.86	245
FMOLS	0.363***	6.14	244
DOLS	0.407***	9.53	238

*Notes: estimated over the cointegrating food–energy relationship established in Table 5. FMOLS and DOLS use a Bartlett kernel with bandwidth 6; DOLS includes three leads and lags. HAC t-statistics. *** p<0.01. FMOLS and DOLS are valid only where a cointegrating relationship exists, and are therefore not applied to the full four-variable system, for which the bounds test in Table 5 rejects cointegration; applied there, FMOLS returns a positively signed dollar coefficient that contradicts both theory and the short-run estimates, which is itself further evidence that no long-run relationship holds among all four series.*

The short-run specification is then subjected to four further checks, reported in Table 10. Replacing the broad energy index with Brent leaves the pattern intact. Using the real (deflated) food index as the dependent variable preserves the signs and significance, with a somewhat stronger supply-chain effect and a lower R^2, as expected once the common inflation trend is removed. Most importantly, adding step dummies for the COVID-19 disruption and the 2022 war barely moves any coefficient, confirming that the results reflect systematic relationships in the data rather than crisis outliers — the parameter-instability concern raised by Al-Maadid et al. (2017).

Table 10. Robustness of the short-run specification (dependent variable: Δ ln Food)

Variant	Δ Energy	Δ Dollar	Δ GSCPI	R^2
(a) Baseline (energy)	0.083***	−0.694***	0.005*	0.52
(b) Brent instead of energy	0.078***	−0.654***	0.005	0.52
(c) Real food index	0.070**	−0.710***	0.008**	0.31
(d) + COVID / war dummies	0.084***	−0.693***	0.005*	0.52

*Notes: each row re-estimates the short-run specification of Table 7. Row (b) replaces the broad energy index with Brent; the two energy measures never appear together. Row (c) uses the real (deflated) FAO index; row (d) adds COVID-19 and war step dummies. HAC t-statistics. *** p<0.01, ** p<0.05, * p<0.10.*

Overall, the robustness analyses confirm that the principal findings remain stable across alternative specifications.

5.6. Sub-index heterogeneity

Aggregated food index analysis shows a lot of heterogeneity in the pass-through of energy prices, corroborating disaggregation approaches developed in the work of Zmami and Ben-Salha (2019). Energy pass-through is seen in the groups of goods connected with the production of biofuels and associated with energy-intensive processes: the vegetable oils (0.201) and sugar (0.182) indices have energy elasticities two- to fourfold higher than those of the aggregate one. Such a phenomenon corresponds to the palm oil/diesel and sugarcane ethanol links. On the contrary, the energy response of downstream groups of animals products is weak, and there is no statistically significant transmission of energy prices in cereals. The dollar effect is negative and significant in all sub-indices. The most pronounced effect was found in vegetable oils (−1.328), the most export-oriented sub-index. Cereals are the only sub-index which showed a clearly positive supply chain effect (0.010), reflecting the grain corridor effects in 2022. Thus, the key result of this paper is the presence of heterogeneity: the food-energy relationship is heterogeneous and not limited to the aggregate level.

Table 11. Heterogeneity of short-run pass-through across FAO sub-indices (dependent variable: Δ ln of each sub-index)

Sub-index	Δ Energy	Δ Dollar	Δ GSCPI	R^2
Cereals	0.047	−0.721***	0.010*	0.26
Vegetable oils	0.201***	−1.328***	0.013**	0.38
Meat	0.044***	−0.353***	−0.001	0.41
Dairy	0.052***	−0.760***	0.004	0.46
Sugar	0.182***	−0.736***	−0.011	0.16

*Notes: each row reports a separate regression in which the short-run specification of Table 7 is re-estimated with the first difference of the log of the stated FAO sub-index as the dependent variable; the regressors are identical across rows. Coefficients are contemporaneous short-run responses, not long-run elasticities. N = 243 in each regression. HAC (Newey–West) t-statistics. *** p<0.01, ** p<0.05, * p<0.10.*

VI. Discussion

6.1. Energy Prices as the Long-Run Driver of Global Food Prices

First of all, according to the estimation results, energy prices are identified as the main determinant of global food prices in the long run. The long-run elasticity estimates that the permanent growth in energy prices is associated with the long-run growth in the FAO Food Price Index, which confirms the importance of energy as an input into the world's food production chain. In contrast to transitory shocks in the market, changes in energy prices have gradual influences on agriculture costs of production through the use of fuel, the production of fertilizers, irrigation, food processing, storage, and transportation, so the influences of energy price shocks could accumulate with time.

This finding is consistent with the work of Shokoohi & Saghaian (2022) who suggest that there are two types of impacts of crude oil prices on food prices – through production cost influences and other macroeconomic influences, including inflation pressures and production decisions. Also, Khan et al. (2022) find that agricultural production costs and biofuel production are the two key transmission mechanisms between oil markets and food markets. Specifically, they find that the growth in crude oil prices increases the profitability of biofuel production from crops such as maize and sugarcane; thus, it decreases the availability of food and increases food prices. The present findings confirm these arguments in that energy price shocks are sufficiently persistent to provide a long-run equilibrium in food prices.

Another important implication of the findings is that the long-run elasticity is sufficiently low because of the imperfect pass-through between energy prices and food prices found by researchers earlier. Ibrahim (2015) finds in his paper that although energy prices have a significant impact on food prices in the long run, the pass-through is imperfect in the sense that the adjustment of food prices to energy prices does not reach one-to-one pass-through because energy accounts for only one share in the structure of the costs of production of agriculture. Agricultural production depends on the climate situation, fertilizer prices, labor costs, technology advancement, government policy, and international trade factors. Therefore, increases in energy prices influence the food prices only partially.

Finally, the heterogeneous nature of energy transmission across commodity groups is an important issue raised by the results of the analysis. The robustness analysis shows much higher energy pass-through in the vegetable oils and sugar sectors than in the meat, dairy, and cereal sectors. This is fully consistent with the findings of Sun et al. (2023) who show that oil market shocks affect different agricultural commodity groups in accordance with different structures of production and market characteristics of these commodity groups. Vegetable oils and sugar are especially strongly associated with the energy market as biofuel feedstock, while livestock products react indirectly through increased feed and transportation costs. Also, Hamouda (2024) suggests that food markets react asymmetrically to oil price changes.

6.2. The Role of the U.S. Dollar in Global Food Price Dynamics

One of the main conclusions made on the basis of the results of the present research is the considerable impact of the U.S. dollar on food prices in the short run. In particular, according to the estimated coefficients, there is a statistically significant drop in the level of the FAO Food Price Index when the Broad U.S. Dollar Index increases. At the same time, there are no indications of the presence of a long-run relationship between the two variables under analysis. Therefore, this result suggests that exchange rate changes work through the adjustment of markets in the short run rather than by changing the equilibrium of global food prices.

The described short-run negative effect can be explained by the role played by the U.S. dollar as the main currency in international commodity pricing. Thus, as Boz et al. (2017) state, almost all internationally traded goods, including food, are invoiced in U.S. dollars despite the currency in which the export is conducted. In other words, the increase in the value of the U.S. dollar results in the higher cost of purchases for those countries which have another currency. It, in turn, leads to the decrease in international demand and food prices in the U.S. dollars.

The current results also support the findings of Bruno and Shin (2019) about the role of the U.S. dollar in global trade. Thus, the authors emphasize the influence of the U.S. dollar on international trade not only through the change in the relative prices but also through the changes in the terms of international financing. Since a considerable part of the global trade is done in U.S. dollars, the increase in the value of the dollar results in the increase in financing costs and tightening of credit terms of trading firms. Therefore, it contributes to the decrease in the amount of trade and demand for commodities and leads to lower international food prices in the short run. So, the importance attached to the dollar in the present research can be explained by both commodity pricing and financing channels.

Finally, the absence of the long-run cointegration of the U.S. dollar and food prices is also quite instructive. Since the fluctuations in exchange rates influence international transactions and commodity markets instantly, the production decisions in agriculture are driven by the structural factors like costs of production, technological advances, climate, etc. As a matter of fact, this conclusion is shared by Kohlscheen (2022) who finds out that pass-through of international food prices to domestic food prices is limited even after controlling for exchange rate effects. In addition, Kartal and Depren (2023) conclude that the exchange rates are a transmission channel through which global shocks affect food prices, but the influence differs over time and depends on market conditions. Finally, Ertuğrul and Seven (2023) show that exchange rate changes explain a considerable part of the gap between international and domestic food prices.

Therefore, the U.S. dollar mainly serves as the transmission channel between global financial market conditions and international food markets in the short run. Energy prices determine the long-run cost structure of food production, whereas the movements in exchange rates influence food prices through the immediate changes in commodity prices, demand, and financing conditions.

6.3. Global Supply Chain Pressures and Heterogeneous Food Price Responses

Based on the empirical evidence, it is clear that there are no statistically significant relations between the aggregate FAO Food Price Index and global supply chain pressures. Initially, this result seems to contradict the existing body of research on the role of global supply chain shocks amid the ongoing Russian–Ukrainian war and the COVID-19 pandemic. However, it is possible to see that global supply chain pressures have a significant impact on certain commodity groups only. In particular, the effects observed for cereals and vegetable oils are positive and statistically significant while there are no significant responses for meat, dairy, and sugar. Thus, the influence of global supply chain pressures is heterogeneous across international food markets.

The reason for such different outcomes can be the dissimilar characteristics of the agriculture sector's supply chains. As stated by Rojas-Reyes et al. (2024), food supply chains involve several stages, namely, production, storage, transportation, processing, and distribution. Therefore, the disruptions might impact various food commodities to varying degrees depending on the production processes and logistics involved. The groups of commodities that are mostly reliant on international logistics network and bulk maritime transport are vulnerable to disruptions of global logistics more than the ones featuring shorter chains of supply or production.

First, the positive response for cereals is in line with the disruptions that are common in international grain markets. The cereals are the most internationally traded goods from the agricultural sector and thus depend on maritime transport and cross-border logistics to a high extent. Hence, any disruption in logistics, including increased prices or transportation delays, influences international prices promptly. Such a result is also in agreement with the arguments of Benigno et al. (2022), who suggest that the Global Supply Chain Pressure Index measures the broad pressures related to increased costs of transportation and production. Additionally, Andriantomanga et al. (2023) state that the bottlenecks in logistics and shortages of inputs are responsible for the rise in inflation caused by global supply chain disruptions.

Likewise, the higher impact of global supply chain pressure index on the vegetable oils can be attributed to the global nature of the edible oil market. It involves a great share of trade in the palm oil, soybean oil, sunflower oil, and rapeseed oil with reliance on maritime transportation. Furthermore, it is worth mentioning that the vegetable oil market faced considerable disruptions after the Russian–Ukrainian war as Ukraine was an important supplier of sunflower oil. As a consequence, the disruptions in international logistics were reflected in international prices of edible oils promptly. Such a conclusion is supported by the findings of Toledo and Duncan (2024) that reveal the significance of supply chain indicators for the forecasting of food price inflation during global crises.

Finally, the nonsignificant effects for meat and dairy products can be attributed to their greater influence of biological production processes and feed cost as compared to the international logistics. Meat and dairy production are characterized by longer production horizon and rigid supply adjustment process, which makes the pass-through of logistic shocks much smaller. Similar to that, it is possible to argue that the nonsignificant effect for sugar is due to the presence of other influential factors, such as energy prices, weather, and biofuels demand.

Summing up the discussion above, it is reasonable to say that global supply chain pressures cannot be considered the universal determinant of the food prices. Instead, their significance depends on the international market integration, transportation intensity, and the characteristics of the commodity market.

6.4. Implications for Global Food Price Formation

In summary, the evidence presented in the study indicates that there is not one major transmission mechanism underlying food prices on a global level; rather, there are several mechanisms operating on different time horizons. In particular, energy prices determine the long-run pattern of changes in food prices through influencing the structural cost of agricultural production. The U.S. dollar exchange rate, on the other hand, affects only the short-run dynamics of commodity prices through the adjustment processes in international trade and market expectations. Additionally, global supply-chain shocks affect food markets differently depending on the characteristics of specific commodity groups.

It should be noted that the results of this study further expand the growing academic discussion that food markets are increasingly becoming integrated with global energy markets and international financial markets, and, therefore, shocks outside the agricultural sector are increasingly being transmitted into the food sector through several economic channels. This conclusion is consistent with the conceptual framework formulated during the literature review phase, in which energy market conditions, international monetary conditions, and global supply chain pressures were recognized as complementary rather than competitive factors that determine food prices.

Heterogeneous reaction of food prices to global shocks according to the FAO food sub-indexes has some methodological importance. Aggregate food price indexes reflect the overall trend in the food market, but they are not able to reflect the differences between commodity sub-groups. For example, cereals and vegetable oils are highly responsive to global supply shocks due to their reliance on international shipping and trade. In turn, the group of livestock related goods is less susceptible to supply shocks because these commodities are characterized by biological cycles and less related to the international logistics.

From the perspective of policy making, the results suggest that a policy designed to stabilize the global food prices needs to be more comprehensive than the agricultural production-oriented policy alone. Agricultural output expansion may not help stabilize the prices in case of the volatility of the energy market, exchange rate movements, and supply chain disruptions. It is necessary to pay attention to enhancing the efficiency of international supply chains, improving trade facilitation measures, monitoring international financial conditions, and addressing logistics bottlenecks.

This policy conclusion becomes particularly relevant considering the growing uncertainty caused by recent geopolitical conflicts, pandemics, and climate change..

VII. Conclusion

The purpose of the present study is to examine the impact of energy prices, US dollar, and global supply chain pressure on global food prices using monthly data with the use of autoregressive distributed lag (ARDL) methodology. This paper contributes to the literature by investigating these three key transmission channels of food prices in one empirical analysis. As a result, the study allows gaining a holistic picture of the determinants of the FAO Food Price Index.

According to empirical evidence, energy prices serve as the most important determinant of global food prices in the long-term perspective as they determine the cost of the entire production and distribution process. At the same time, US dollar serves as the main determinant of food prices in the short term through international pricing and transmission channels. Finally, even though global supply chain pressure does not have a significant impact on the aggregated FAO Food Price Index, robustness analysis proves its relevance at the level of commodity subgroups. More specifically, cereal and vegetable oil prices prove to be more sensitive to disruptions in supply chains than meat, dairy, and sugar prices.

These findings are relevant as they consider three global indicators in the same empirical model instead of separating each of them. In addition, these findings highlight the possibility of hidden heterogeneity at the commodity level when using aggregated food price indices in the analysis of global shocks. In turn, this means that a separate analysis of various commodities can help in understanding their peculiarities and impacts better.

In terms of policies, this paper proves that food price stability requires not only instruments aimed at regulation of agriculture production but also monitoring of development in energy markets, exchange rates, and global supply chains as well. For future research, one may consider incorporating different global risk indicators, climate-related variables, or commodity-level analyses to enrich our understanding of food prices.

Despite these contributions, there are some limitations associated with the paper. First of all, the analysis relies on aggregate global food prices which are captured by the FAO Food Price Index and, therefore, cannot take into account all market features specific for each individual commodity. Second, while robustness analysis relies on major FAO sub-indices, it does not consider many others such as extreme weather events, fertilizers, or climate-related shocks. In future research, these elements might be incorporated either directly into the empirical model or considered with the use of nonlinear approach.

As global food markets become increasingly interconnected with energy markets, financial conditions, and international supply chains, understanding these transmission channels will become increasingly important for ensuring global food security and market stability.

Funding Statement: No funding was received

Conflict of Interest Statement: The authors declare that they have no known financial or non-financial competing interests that could have appeared to influence the work reported in this paper.

Declaration of Generative AI Use: In the writing process of this manuscript, ChatGPT (OpenAI) has been used in order to improve the clarity, grammar, and readability of the text. It should be noted that the mentioned AI program was not applied for collecting, analyzing the data, and making conclusions of a scientific nature. Responsibility for the content of the manuscript lies with the authors of the article.

Data Availability Statement: The datasets that have been used for the current study are those obtained from open-access databases as mentioned in the paper. The combined dataset, including additional information, can be obtained from the corresponding author on request.

Author Contributions: Conceptualization: Mine Sönmezay, Yağız Dereboy; Methodology: Mine Sönmezay, Yağız Dereboy; Formal Analysis: Mine Sönmezay, Yağız Dereboy; Investigation: Mine Sönmezay, Yağız Dereboy; Data Curation: Mine Sönmezay, Yağız Dereboy; Writing – Original Draft: Mine Sönmezay, Yağız Dereboy; Writing – Review & Editing: Mine Sönmezay, Yağız Dereboy. All authors have read and approved the final version of the manuscript.

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